Efficient multi-class fetal brain segmentation in high resolution MRI reconstructions with noisy labels – Supplementary Material

Kelly Payette[1], Raimund Kottke[2], Andras Jakab[1]
[1] Center for MR-Research, University Children's Hospital Zurich, Zurich, Switzerland,
kelly.payette@kispi.uzh.ch
[2]Diagnostic Imaging and Intervention, University Children's Hospital Zurich, Zurich Switzerland

1 Neural Network Details

A 2D U-Net based on [1] was used in our work. It was created using keras v2.2.4 in Python 3.6.8. The network was trained using a Quadro P6000 with 24GB of RAM. An Adam optimizer was used with a learning rate of 1E-5. The generalized dice coefficient was used as a loss function [2]. The ReLu activation function was used for every convolutional layer except the final, where softmax was used. L2 regularization was used in every layer except the final layer, where no regularization was used. Batch normalization was used after every convolutional layer, and a dropout layer (0.5) was used in every block of convolutional layers within the U-Net, except the first block where a dropout layer (0.25) was used. See Fig. 1 for network details.

The images being fed into the network were 256x256, 1 channel, and a batch size of 16 was used. A total number of 8 classes were defined (external cerebrospinal fluid, grey matter, white matter, ventricles, deep grey matter, cerebellum, brain stem, background). The network was trained for 100 epochs, with early stopping in place if the model did not improve after 10 epochs. A testing size of 20% was chosen while training, shuffling the training and testing data each epoch.

When transfer learning was occurring, the weights for all layers except the last SoftMax layer and last convolutional layer were initialized with the weights created in Network 1 and frozen.

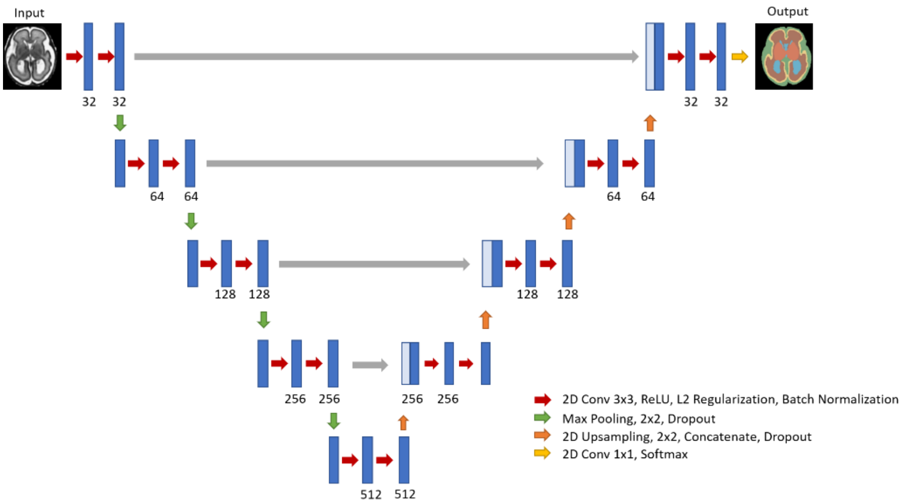

Fig. 1. Overview of the neural network (U-Net) used. The number underneath each block indicates the number of channels.

2 References

1. Ronneberger, O., Fischer, P., Brox, T.: U-Net: Convolutional Networks for Biomedical Image Segmentation. In: Navab, N., Hornegger, J., Wells, W.M., and Frangi, A.F. (eds.) Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015. pp. 234–241. Springer International Publishing, Cham (2015). https://doi.org/10.1007/978-3-319-24574-4_28.
2. Sudre, C.H., Li, W., Vercauteren, T., Ourselin, S., Jorge Cardoso, M.: Generalised Dice Overlap as a Deep Learning Loss Function for Highly Unbalanced Segmentations. In: Cardoso, M.J., Arbel, T., Carneiro, G., Syeda-Mahmood, T., Tavares, J.M.R.S., Moradi, M., Bradley, A., Greenspan, H., Papa, J.P., Madabhushi, A., Nascimento, J.C., Cardoso, J.S., Belagiannis, V., and Lu, Z. (eds.) Deep Learning in Medical Image Analysis and Multimodal Learning for Clinical Decision Support. pp. 240–248. Springer International Publishing, Cham (2017). https://doi.org/10.1007/978-3-319-67558-9_28.